

[MVA] - Rapport de stage

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Goodhart's law

When a metric becomes a target,
it ceases to be a good metric.

1 Introduction

Continual learning is a machine learning paradigm that focuses on the ability of a model to learn and adapt to new information over time, without forgetting previously learned knowledge. It is particularly relevant in scenarios where data is non-stationary or arrives in a sequential manner. By leveraging techniques such as online learning, regularization, and knowledge distillation, continual learning enables models to continuously update their knowledge and improve performance as new data becomes available.

1.1 Initial project

1.1.1 Project statement

In this context, the aim of the project was initially stated as follows:

Catastrophic forgetting is a major challenge in continual learning systems, where a neural network needs to adapt to new tasks that differ from what it has previously learned. To tackle this, experts have devised strategies to either keep the neural network's critical weights intact or use generative models to refresh the network's memory of past tasks. However, these methods aren't perfect for hardware implementation due to their additional memory demands or the need for a separate network that constantly rehearses past information.

Meanwhile, we understand that a system's architecture significantly impacts its ability to generalize knowledge. Enter Gradmax [4], an innovative algorithm that simultaneously optimizes a network's structure and weights, and smartly allocates neurons for new tasks without disrupting existing knowledge. This method is memory and computation efficient, making it suitable for hardware applications. But it does require hardware capable of dynamically adjusting its architecture to integrate new neurons as needed. Our recent work has led to a flexible hardware architecture, Mosaic [1], with multiple cores that can rearrange their connections in real-time.

The aim of this project is to explore the integration of Gradmax with our dynamic 'Mosaic' architecture. We plan to approach this by factoring hardware limitations into the optimization process. In addition, we're considering the development of a gating network within this architecture that determines the optimal timing for assigning tasks to newly added neurons. This could leverage cutting-edge techniques like Mixture of Expert models [2].

Let's dissect this project statement to understand the main objectives and challenges it encapsulates.

Computational costs. The project aims to address the computational costs associated with continual learning methods. Thus we expect to have a way to measure this cost, employ as figure of merit

or integrate it to the optimization process and to compare it to the cost of other methods.

Continual learning approach. Literature categorizes continual learning approaches into three main categories: rehearsal, regularization, and architectural. However in the process of taking into account the computational costs, we will explore the architectural approach.

Gradmax Gradmax is a method designed for learning on a single task. Thus this project invites to extend it to continual learning.

Mosaic In the process of adapting Gradmax method to the continual learning framework, we will have to consider the hardware constraints of the Mosaic architecture.

1.1.2 Major issues

In the very beginning of the project, we faced two major issues. The first one is a consequence of Gradmax paper misleading introduction. Indeed, in the very first paragraph of the paper, the authors introduces :

Searching for the best architecture for a given task is an active research area with diverse approaches.[...] Most of these approaches are costly, as they require large search spaces or large architectures to start with. In this work we consider an alternative approach.

The genuine expectation regarding the work following such an introduction is that the authors will provide an innovative method that factorizes architecture search in the optimization process of learning a task while avoiding to train numerous high-size architectures, which is computationally expensive.

However, contrary to expectations, GradMax falls short at enabling neural architecture optimization. The method consists in growing a network from a root architecture to a predetermined target architecture, by adding neurons to it through training epochs. It focuses on the initialization of added neurons (the *how*), neglecting the crucial questions of *when* and *where* to add them, which are deferred for future research. In the paper, the decisions regarding *where* and *when* to add neurons are predetermined and take the form of a schedule established. Consequently, it's challenging to conclude that the GradMax framework effectively enables architecture optimization for growing artificial neural networks.

Additionally, authors do not consider the computational cost of their method in the rest of the paper. This is a major issue as the project was initially designed to reduce the computational cost of continual learning methods.

1.1.3 Additional hurdles

As a general concept, we consider that continual learning refers to the ability of a model to learn and adapt to new information over time, without forgetting previously learned knowledge. However, this wide definition encompasses a variety of scenarios. First, it can be the case that there is no explicit task boundary, and the model must continuously adapt to new data without any indication of when a new task begins. This is known as incremental learning. Second, the model may be presented with a sequence of tasks, each with its own training data and objectives. In this case, the model must learn each task sequentially and adapt to new tasks without forgetting the previous ones, which is known as sequential learning. Third, the model may be presented with a series of tasks that are related or have some shared structure. In this case, the model must leverage this shared structure to learn new tasks more efficiently. This is known as multitask learning.

But even after this specification, ambiguities persist. For instance when it comes to sequential learning, some frameworks assume that the model knows when a new task arrives, whereas others do not make this assumption.

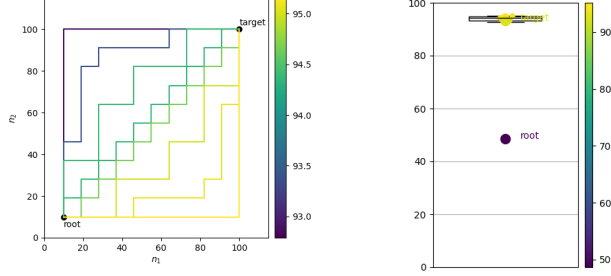
1.2 Revised project

2 Attempted approaches

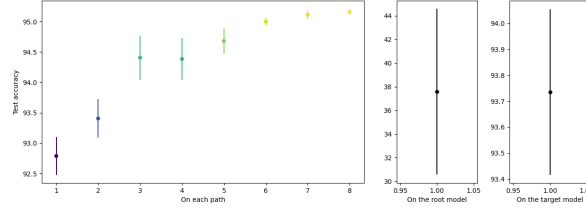
2.1 LoRA

2.2 Motivating growth exploration

Trying to tackle the questions of where and when to grow neurons in the framework of GradMax, that is, starting with a root architecture and converging to a target architecture, it can be interesting to assess whether or not the way we grow the architecture toward this target architecture matters. For example, we can consider a simple two-hidden layer architecture, and grow it by adding neurons to the first hidden layer first, then to the second hidden layer, or the other way around. So the order we add neurons to each layer define a path. And we can ask ourselves if some paths are more efficient than others.



(a) Average test accuracy (b) Average test accuracies of achieved by following each the paths, the root model and paths to grow the network, the target model, across 5 trials across 5 trials



(c) Average test accuracy across 5 trials, with standard deviation

Figure 1: Results on MNIST with GradMax initialization

To do so, we set the root network (RN) to be a two-hidden-layer MLP with 10 neurons on each layer, and the target network (TN) to be a two-hidden-layer MLP with 100 neurons on each layer. As reference for comparison, we train both RN and TN on 300 batch MNIST batches, each of which is of size 128, for 3 epochs. We use Adam optimizer with learning rate equal to 5×10^{-3} , and mean squared error loss function. We repeat this process 5 times for statistical reliability. See 1c for the results.

Then, in the processus of growing RN toward TN through the training process, we define schedules. Each schedule consists 20 growth step. 10 of these growth steps consist in adding 9 neurons to the first and the other 10 growth steps consist in adding 9 neurons the second hidden layer. Thus, the only way two schedules differ from each other is this order it plans to grow each layer. As for training RN and TN, the growing process occurs while training on 300 batch MNIST batches, each of which is of size 128, for 3 epochs. Overall, each growth of 10 neurons happens once every We use Adam optimizer with learning rate equal to 5×10^{-3} , and mean squared error loss function.

That being said, we can see that the path we choose to grow the network has a significant impact on the final test accuracy. In particular, the path that consists in adding neurons to the first hidden layer first, then to the second hidden layer, seems to be the most efficient.

Thus, exploring neurogenesis makes sense in the context of traditional learning (on a single task). However, what we want to do is to adapt this to a continual learning framework. That is, we want to grow the network

2.3 Growth in continual learning

2.4 Conclusions we can draw from these attempts

To this regard, as a general concept, we can control :

- how the added neurons react to new task samples
- how the old neurons react to new task samples
- (depending on the approach) how the old neurons react to previous tasks samples

However, we have absolutely no control over the way the added neurons react to previous tasks samples because :

- we have no access to previous tasks samples
- we are not using any rehearsal strategy
- we do not intend to encode any information about the specificity of previous tasks in the weights

So our very last hopes without memory are :

- to parametrize/constrain the weights so that they encode task information

Interestingly, these questions and remarks we have been objecting to ourselves about foundations of our approach applies to several other approaches. Approaches like LoRA, EWC, neural growth (whether initialization is done through GradMax or TINY) are condemned to fail in the context of continual learning. While they have no information about previous tasks samples, they will be limited to trade offs and hyperparameter optimization.

References

- [1] Thomas Dalgaty et al. “Mosaic: in-memory computing and routing for small-world spike-based neuromorphic systems”. In: *Nature Communications* 15.1 (Jan. 2024). ISSN: 2041-1723. DOI: 10.1038/s41467-023-44365-x. URL: <http://dx.doi.org/10.1038/s41467-023-44365-x>.
- [2] David Eigen, Marc’Aurelio Ranzato, and Ilya Sutskever. *Learning Factored Representations in a Deep Mixture of Experts*. 2014. arXiv: 1312.4314 [cs.LG].
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- [4] Utku Evci et al. *GradMax: Growing Neural Networks using Gradient Information*. 2022. arXiv: 2201.05125 [cs.LG].
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- [6] Javier Lopez Randulfe and Leon Bonde Larsen. *A multi-agent model for growing spiking neural networks*. 2020. arXiv: 2010.15045 [cs.NE].
- [7] Xin Yuan, Pedro Savarese, and Michael Maire. *Accelerated Training via Incrementally Growing Neural Networks using Variance Transfer and Learning Rate Adaptation*. 2023. arXiv: 2306.12700 [cs.LG].

Appendix

2.5 Other results for motivating exploration of growth paths

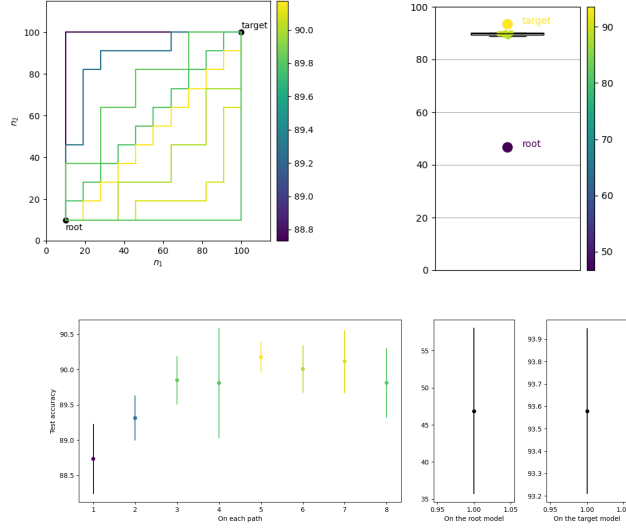


Figure 2: Results on MNIST with random initialization

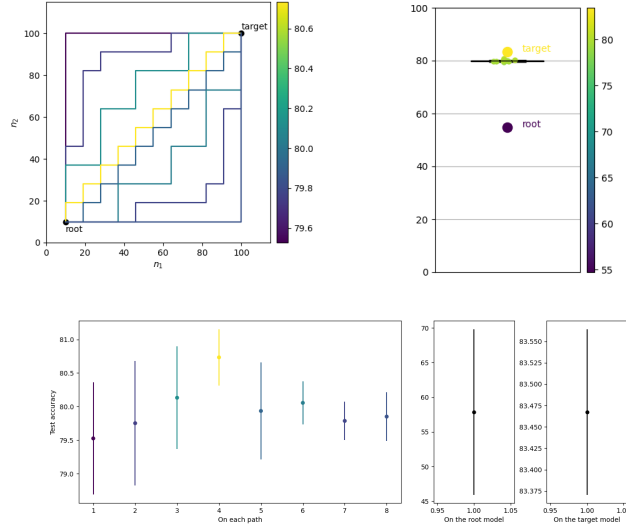


Figure 3: Results on FMNIST with random initialization

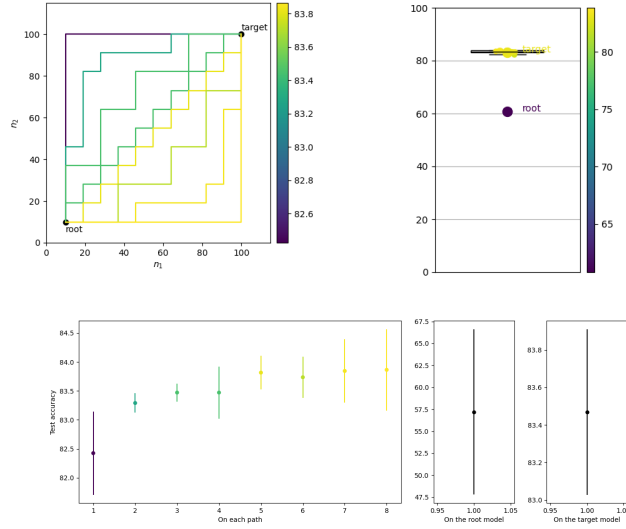


Figure 4: Results on FMNIST with gradmax initialization

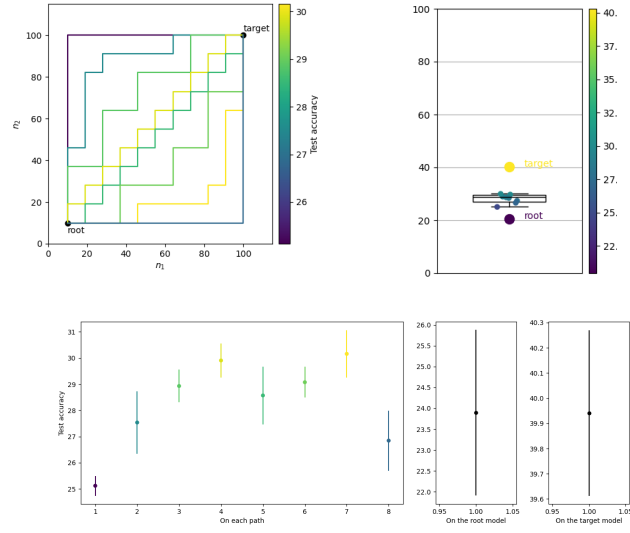


Figure 5: Results on CIFAR10 with random initialization

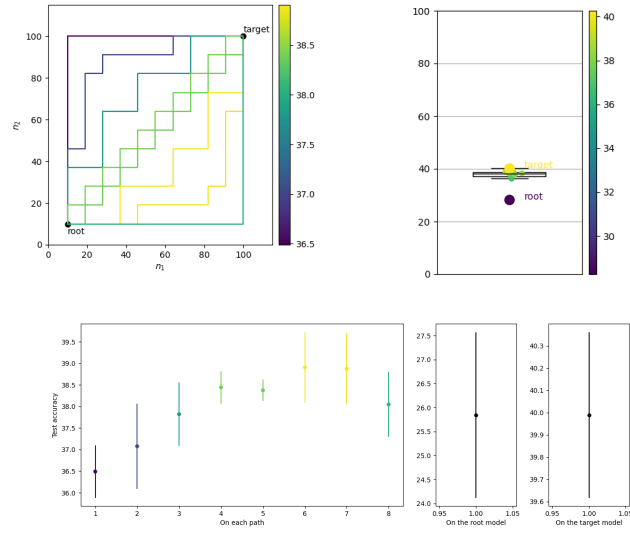


Figure 6: Results on CIFAR10 with gradmax initialization